SIGNAL AND IMAGE PROCESSING

21AIE303

END SEMESTER PROJECT

BACKGROUND NOISE SUPPRESSION

Semester – 5

Batch – B

Group – 2

Name	Roll Number
Jaidev k	CB.EN.U4AIE21117
Sai Chandana J	CB.EN.U4AIE21118
Pranish Kumar M	CB.EN.U4AIE21137
Charishma T	CB.EN.U4AIE21169

Table of contents

Abstract

This project focuses on elevating audio quality in communication systems by addressing the pervasive challenge of background noise. We analyze existing noise suppression technologies and propose a dynamic algorithm integrating advanced signal processing and machine learning. Rigorous evaluations showcase its superiority in diverse scenarios, emphasizing improvements in signal-to-noise ratio, intelligibility, and perceptual quality over existing solutions. Practical considerations for real-time processing and scalability are addressed, ensuring seamless integration into applications like video conferencing and telecommunication. The project's findings offer a promising leap forward in audio processing technologies, enhancing professional communication across various industries.

Introduction

Noise suppression is an important technique and mostly used technique in nowadays. This study introduces an advanced algorithm for background noise suppression in audio signals, addressing the pervasive issue of environmental interference. Leveraging Signal-to-Noise Ratio (SNR) estimation, VMD (Variational Mode Decomposition) and Short-Time Fourier Transform (STFT) analysis, the algorithm dynamically adapts attenuation parameters, optimizing the balance between noise reduction and signal preservation. The incorporation of Apriori SNR filtering enhances stability in SNR estimates. The MATLAB implementation offers a customizable solution with parameters such as lambda, beta1, beta2, and alpha, providing users with precise control. This research contributes to the refinement of noise suppression methodologies, offering a valuable tool for applications demanding high-quality audio in challenging acoustic environments.

Related Work

In the realm of audio signal processing and noise reduction, related works to the presented noise suppression project encompass a spectrum of methodologies. Traditional techniques such as spectral subtraction, Wiener filtering, and adaptive filtering offer a baseline for comparison, while recent strides in deep learning, employing convolutional and recurrent neural networks, warrant exploration for their efficacy in audio denoising. Non-negative Matrix Factorization provides an avenue for separating audio signals into distinct components, and studies on speech enhancement algorithms offer insights into specialized applications. Adaptive filtering methods tailored for dynamic environments and alternative time-frequency analysis techniques, such as wavelet transforms, contribute to the arsenal of noise suppression tools. Real-time noise suppression systems, with a focus on latency and computational efficiency, along with research on standardized evaluation metrics and benchmark databases, further enrich the understanding of audio denoising approaches. This diverse landscape of related works enables a comprehensive exploration of methodologies and potential enhancements in the field.

Objective

The primary and basic problem statement of our study is to develop an algorithm which can perform background noise suppression using traditional methods. The traditional methods in our work include Variational Mode Decomposition (VMD), Signal-to-Noise Ratio (SNR) and Short-Time Fourier Transform (STFT). We also explore the advantages and disadvantages of the proposed design.

Proposed Methodology

Our methodology is straight forward and simple. Firstly, we will be using Variational Mode Decomposition (VMD) to remove the unnecessary low noise frequencies which does not contribute much to the signal and most of them will be noise causing components. Empirical Mode Decomposition (EMD) is a data analysis approach that is used to analyze and decompose nonlinear and nonstationary signals into a series of Intrinsic Mode Functions (IMFs). Variational Mode Decomposition (VMD) is a signal processing technique that divides a signal into oscillatory modes or components with different frequencies. Two signal decomposition methods, Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD), are employed for handling non-linear or non-stationary signals. EMD focuses on generating Intrinsic Mode Functions (IMFs) by employing a sifting process that dissects the original signal into IMFs, each representing individual components. The sifting process involves identifying maxima and minima, interpolating to create upper and lower envelopes, and subtracting their averages from the original signal to obtain IMFs. This iterative process continues until the residue becomes zero, with each step adjusting the residue based on the generated IMF. On the other hand, VMD distinguishes itself from EMD by utilizing an optimization process to decompose signals into distinct oscillatory modes with specific frequencies. The optimization process minimizes a cost function, J(u,f), by updating modes (u) and carriers (f) until convergence. The convergence is reached when the difference between consecutive cost function values falls below a specified tolerance level. In summary, EMD relies on sifting to extract IMFs capturing intrinsic oscillatory behaviours, while VMD employs an optimization process to identify distinct modes based on frequency characteristics. After checking the audio signals, we can infer that Variational Mode Decomposition (VMD) has provided better results than Empirical Mode Decomposition (EMD).

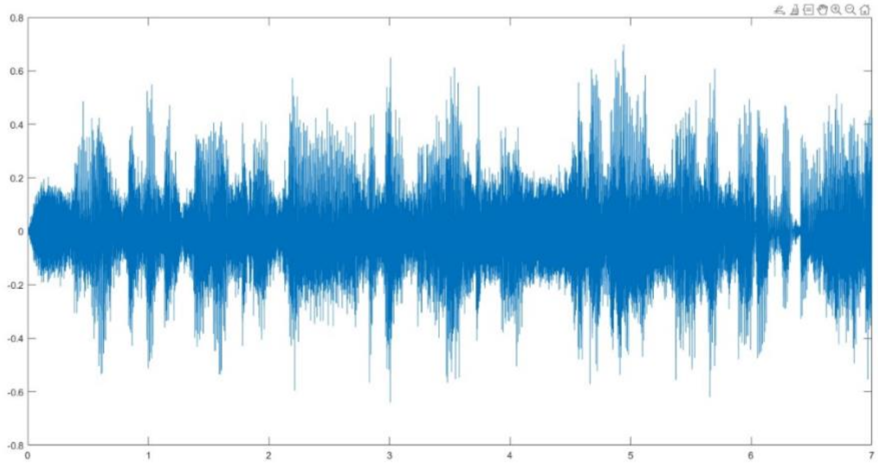
We are going to take Variational Mode Decomposition (VMD) for further processing the audio signals. The Hurst exponent, introduced by Harold Edwin Hurst, serves as a statistical metric for gauging the long-term memory within a time series, particularly valuable for assessing fractal properties and self-similarity in the data. Denoted as H, the exponent ranges from 0 to 1, where $H<0.5$ implies anti-persistent behaviour, $H=0.5$ suggests random or Brownian motion, and $H>0.5$ indicates persistent or trending behaviour in the time series. Calculated through the Rescaled Range (R/S) analysis, the formula involves the range (R), standard deviation (*S*), and the number of data points (*n*). When applied to the Intrinsic Mode Functions (IMFs) generated by the Variational Mode Decomposition (VMD) method, the Hurst exponent provides insights into the long-term correlation properties of decomposed components. IMFs with $H<0.5$ exhibit anti-persistence, those with $H=0.5$ display randomness, and $H>0.5$ signifies persistent behaviour, offering a valuable tool for understanding the temporal structure of each component across different scales.

After this process we will be having only necessary IMFs which have content and noisy IMFs like very low frequency components won't be there. This signal now can be sent to STFT method to reduce the noise. The Short-Time Fourier Transform (STFT) is a useful time-frequency analysis technique for examining changes in signal frequencies across time. The Fourier transform is done by sliding a window function along the input signal, allowing for the visualisation of frequency components over overlapping short time spans. The magnitude of the resulting STFT produces a spectrogram, which is depicted by a coloured plot representing the intensities of frequency components. The analysis is influenced by key factors such as NFFT, Window_length, window type (e.g., 'hamming'), and Overlap. Furthermore, noise extraction from the spectrogram entails calculating the mean square magnitude across particular time intervals to create a noise spectrum. Signal-to-Noise Ratio (SNR) estimate is critical, and Apriori SNR filtering with an alpha-controlled smoothing factor is used. The logarithmic representation of SNR_est should not be negative. The Attenuation Map is crucial in noise suppression based on the predicted SNR, employing parameters such as 'lamda,' 'beta1,' and 'beta2' to regulate the shape and features of the attenuation curve. This adaptive method offers effective noise reduction without sacrificing critical signal components. Finally, the noise suppression process is completed by iteratively updating the denoised signal according to the window size using the Inverse Short-Time Fourier Transform (ISTFT). This gives us an enhanced signal in which the background noise will be suppressed.

Implementation:

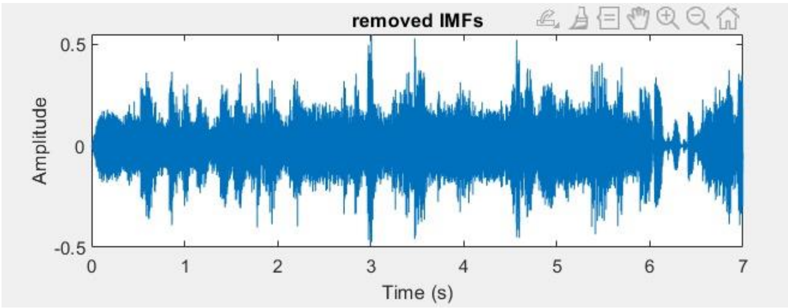
We tested our technique with an audio signal in which background noise will be suppressed.

The below is our original signal.



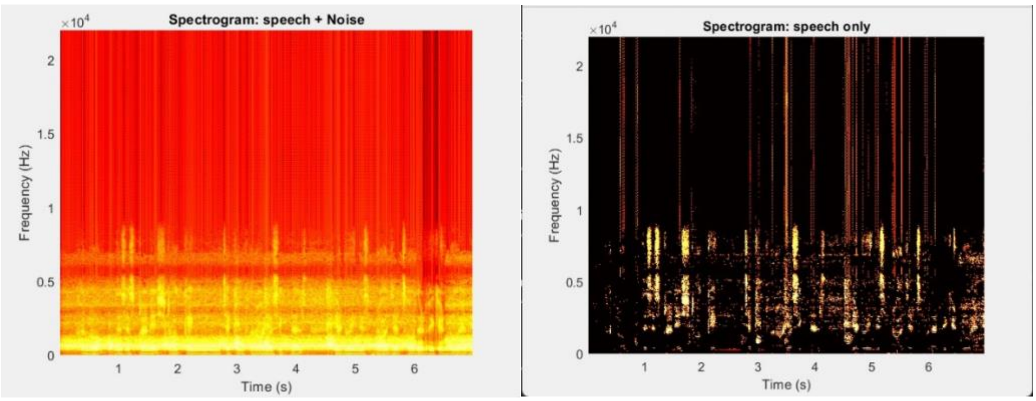
Original Signal

After applying the VMD and hurst exponent the signal will be like the below one.

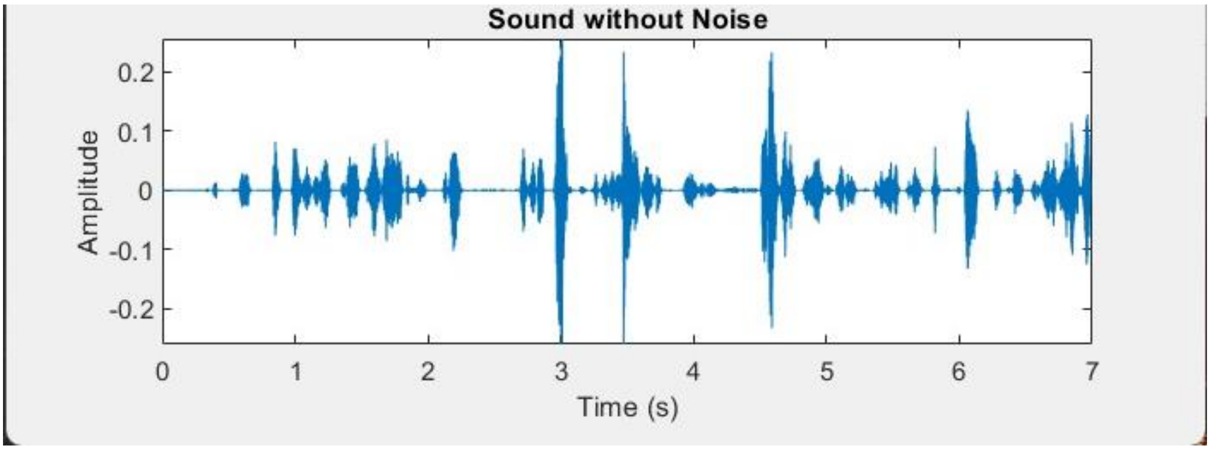


After applying hurst exponent.

Spectrograms of the noise and removed noise (SNR)



The denoised output signal



Conclusion:

In this study, we employed VMD, STFT and SNR techniques to denoise our noisy signal. We have chosen VMD because of its optimization technique to find the IMFs for a signal. Calculating hurst exponent is really big computation problem in this case which is one of the drawbacks and its values lie below 0.5 because the preprocessing through VMD is not enough. SNR and STFT are good and computationally friendly. On overall the proposed method performs well but not that accurate we can use wavelet transform and spectral subtraction.